



Review of modern technologies for assessing knowledge and professional competencies in higher online education

O.Yu. Digtyar¹, N.G. Kondrakhina², T.A. Tantsura³, E.E. Kuvshinova⁴

Financial University under the Government of the Russian Federation,
Moscow, Russian Federation.

E-mail: ¹OYDigtyar@fa.ru; ²nkondrakhina@fa.ru; ³ttancyra@yandex.ru; ⁴EEKuvshinova@fa.ru

✉ OYDigtyar@fa.ru

Abstract. *Introduction.* The digital transformation of higher education and the expansion of online learning formats have highlighted the need to revise established models of pedagogical assessment. Ensuring the validity and reliability of distance assessments is essential for maintaining academic standards and sustaining students' cognitive engagement. *Aim.* The present study aims to conduct a comparative analysis of Russian and international assessment technologies within the higher online education system. *Methodology and research methods.* The comparison was conducted according to four criteria: accessibility of tools, adaptability to individual learning trajectories, interactive potential, and the applicability of results within the professional domain. Particular attention was paid to the limitations of extrapolating international models into Russian pedagogical practice, taking into account national educational specificities. The study employed methods of comparative analysis and typologisation of assessment tools. *Results.* The advantages and limitations of various assessment approaches are analysed, along with their impact on the quality of education and student motivation. It is demonstrated that the Russian distance education system, while actively incorporating advanced international practices, retains distinctive characteristics shaped by national cultural and pedagogical traditions. *Scientific novelty.* The scientific novelty resides in the systematisation of criteria for comparing diverse assessment systems and in substantiating the adaptive potential of international approaches for Russian higher education. *Practical significance.* The practical significance of the research findings is demonstrated by the development of a framework of recommendations for educational policymakers, university administrators, academic staff, and designers of EdTech solutions.

Keywords: higher education, online education, assessment technologies, comparative education, digital didactics, educational platforms, adaptive testing, Russian EdTech market

For citation: Digtyar O.Yu., Kondrakhina N.G., Tantsura T.A., Kuvshinova E.E. Review of modern technologies for assessing knowledge and professional competencies in higher online education. *Obrazovanie i nauka = The Education and Science Journal*. 2026;28(9). doi:10.17853/1994-5639-2026-5311

Обзор современных технологий оценивания знаний и профессиональных компетенций в системе высшего онлайн-образования

О.Ю. Дигтяр¹, Н.Г. Кондрахина², Т.А. Танцура³, Е.Е. Кувшинова⁴
Финансовый университет при Правительстве Российской Федерации,
Москва, Российская Федерация.

E-mail: ¹OYDigtyar@fa.ru; ²nkondrakhina@fa.ru; ³ttancyra@yandex.ru; ⁴EEKuvshinova@fa.ru

✉ OYDigtyar@fa.ru

Аннотация. Введение. Цифровизация высшего образования и экспансия онлайн-форматов обучения актуализируют проблему пересмотра устоявшихся моделей педагогического контроля. Обеспечение валидности и надежности дистанционного оценивания выступает условием сохранения академических стандартов и поддержания познавательной активности обучающихся. Цель – провести сравнительный анализ отечественных и зарубежных технологий оценивания в системе высшего онлайн-образования. *Методология, методы и методики.* Сопоставление проведено по четырём критериям: доступность инструментария, адаптивность к индивидуальным траекториям, интерактивный потенциал и применимость результатов в профессиональной сфере. Особое внимание уделено пределам экстраполяции международных моделей в российскую педагогическую практику с учетом национальной образовательной специфики. В работе использованы методы компаративистского анализа и типологизации оценочных средств. *Результаты.* Проанализированы преимущества и ограничения различных подходов к оцениванию, а также их влияние на качество образования и учебную мотивацию студентов. Показано, что российская система дистанционного образования, активно интегрируя передовые международные практики, сохраняет уникальные черты, обусловленные национальными культурными и педагогическими традициями. *Научная новизна* заключается в систематизации критериев сопоставимости разноплановых систем оценивания и обосновании адаптационного потенциала зарубежных подходов для российской высшей школы. *Практическая значимость* результатов состоит в формировании рекомендательной базы для разработчиков образовательных политик, административных команд вузов, преподавательского корпуса и проектировщиков EdTech-решений.

Ключевые слова: высшее образование, онлайн-обучение, технологии оценивания, сравнительная педагогика, цифровая дидактика, образовательные платформы, адаптивное тестирование, российский рынок EdTech

Для цитирования: Дигтяр О.Ю., Кондрахина Н.Г., Танцура Т.А., Кувшинова Е.Е. Обзор современных технологий оценивания знаний и профессиональных компетенций в системе высшего онлайн-образования. *Образование и наука.* 2026;28(9). doi:10.17853/1994-5639-2026-5311

Introduction

The current system of higher education is undergoing profound transformation driven by the digitalisation of social relations and the rapid evolution of information and communication technologies. Online education, once considered a niche mode of delivery, now constitutes a major developmental vector for universities, educational platforms, and corporate training centres. The massive shift to remote formats during the COVID-19 pandemic, on the one hand, confirmed the technological feasibility of conducting education in a digital environment; on the other hand,

it exposed systemic issues related to student assessment. Traditional control methods – in-person examinations, oral questioning, and written assignments – have largely lost their effectiveness and applicability in distance settings.

Thus, a contradiction exists between the need for objective, reliable, and motivating assessment in online environments and the insufficient development of appropriate control technologies. This contradiction defines the relevance of the present study.

Research aim – to conduct a comprehensive comparative analysis of student knowledge assessment technologies in online higher education in Russia and abroad, to identify the most effective practices, and to determine pathways for their adaptation to the conditions of the Russian educational system.

Research questions. In accordance with the stated aim, the following research questions are formulated:

1. Which student assessment technologies are used in online higher education practice in Russia and abroad?
2. What specific features of their implementation are determined by cultural, pedagogical, and institutional factors?
3. Which control methods are most effective for assessing different types of competencies (from subject-specific to metacognitive) in a distance environment?
4. How can academic integrity and personalised feedback be ensured when using digital assessment tools?

Study limitations. The following limitations are acknowledged:

- *Dynamic nature of the subject:* the rapid evolution of the EdTech market and AI technologies means that certain described tools may undergo substantial changes in the near future.
- *Content boundaries:* the study deliberately excludes assessment technologies in secondary vocational and continuing education (except where directly relevant to higher education). It also does not separately address cognitive biases in automated assessment instruments.
- *Empirical base:* the analysis relies on available open publications by Russian and international authors (predominantly from the last 5–7 years), which does not fully capture the implementation practices in individual universities or closed corporate institutions.
- *Methodological constraint:* the comparative analysis is conducted at the level of synthesising published data without a large-scale experimental study, requiring verification of the findings in subsequent work.

Despite these limitations, the analysis provides a representative overview of the current state of the problem and identifies directions for further research into pedagogical measurement in digital learning environments.

Methodology, Methods, and Research Procedures

This study is of a comprehensive interdisciplinary nature, which necessitated the integration of several methodological approaches and empirical methods.

The theoretical and methodological foundation comprises three interrelated approaches: systemic, comparative, and analytical. Their selection is determined by the multi-faceted nature of the object of study – the transformation of assessment technologies in online education – which cannot be adequately described within a narrow disciplinary framework.

The systemic approach serves as the fundamental ontological framework. Within this approach, assessment technologies are interpreted not as an isolated set of testing instruments but as an inherent component of the overall educational ecosystem, reciprocally linked to learning objectives, course content, student motivation, the level of digital competence among teaching staff, and the technical provision of the learning process. This perspective allows for the identification of both direct and feedback loops between assessment procedures and other elements of the pedagogical system.

The comparative approach is the leading research strategy, as the study's aim requires an objective juxtaposition of domestic and foreign assessment practices in the digital educational environment. The application of the comparative method made it possible to reveal not only universal (invariant) patterns in the evolution of knowledge control systems but also nationally specific features shaped by differences in educational traditions, regulatory frameworks, the degree of institutionalisation of EdTech solutions, and the level of digital maturity of educational systems.

To address the research tasks, a set of complementary methods at both empirical and theoretical levels was employed. *Theoretical analysis and synthesis*. In the first stage, a systematic review was conducted of Russian and international scientific literature (including publications indexed in Scopus and Web of Science), normative legal acts in higher education, federal state educational standards (FSES 3++), and technical and methodological documentation from leading EdTech platforms. The source analysis enabled the construction of a conceptual framework, the operationalisation of key concepts (“digital assessment”, “adaptive testing”, “e-portfolio”), the identification of empirically unsubstantiated claims, and the detection of gaps in current scientific knowledge. The synthesis of analytical data facilitated the systematisation of disparate information on assessment technologies and the construction of a typology according to criteria of objectivity, automation, and functional role in the learning process.

Comparative analysis (comparativistics). This method was implemented at two levels:

- *Micro-level* – comparison of individual assessment technologies (testing, project-based work, portfolio, peer assessment, adaptive testing) according to a criteria system including objectivity, reliability, validity, resource intensity (labour and technical costs), impact on academic motivation, and the degree to which stated competencies are developed.

- *Macro-level* – comparative analysis of established assessment practices in the higher education system of the Russian Federation and leading foreign countries (USA, EU member states). The source base comprised scientific publications,

open statistical data on the functioning of educational platforms (Coursera, edX, Stepik), and analytical reports from international organisations (OECD, UNESCO, European Commission).

Case study analysis. Examples of the implementation of hybrid learning and assessment models in several Russian universities (with anonymity preserved at the request of informants) and on specialised online platforms were examined. The use of case studies allowed the identification of three types of practical barriers: a) technical constraints (insufficient bandwidth, incompatibility of LMS with internal university information systems); b) organisational resistance from some teaching staff, due to a lack of motivation and digital competencies; c) institutional deficit – the absence of systematic professional development programmes in the design of digital assessment tools.

Auxiliary methods

- *Generalisation* – used to catalogue and systematise identified facts and empirical patterns, as well as to move from individual observations to general statements.
- *Pedagogical modelling* – applied to construct predictive scenarios for the development of the online education market in the Russian Federation (moderate extensive growth, innovative explosive growth, stagnation under current institutional conditions). Scenario modelling was conducted taking into account exogenous factors (regulatory policy, regional digitalisation levels) and endogenous resources of the educational system.

The choice of these methods is justified by the research aim, which is not merely a descriptive account of existing practices but rather an identification of their internal logic, an assessment of comparative effectiveness, recognition of drivers and barriers, and the determination of promising directions for the evolution of assessment technologies in the digital educational environment.

Results

The digital transformation of higher education, accelerated by the global challenges of the early 2020s, has led to a paradigm shift in pedagogical measurement. Traditional forms of summative assessment (examinations, testing) show limited validity in asynchronous online learning and distributed cognitive environments. The purpose of this review is to systematically and critically analyse the key technological directions shaping the current landscape of e-assessment, from the perspectives of didactic effectiveness, algorithmic soundness, and ethical acceptability. The question of the educator's role in a learning environment altered by artificial intelligence (AI) technologies was already being raised before the advent of publicly available generative models [1]; new challenges for teachers are documented in reviews of AI application practices in universities [2; 3].

Each technological cluster below is discussed in relation to the corresponding research questions.

Artificial intelligence and large language model technologies: from discrete scoring to semantic analysis

The evolution of automated systems is characterised by a move away from the dichotomous (“correct/incorrect”) model towards context-dependent semantic assessment. An empirical study conducted on the basis of the Russian integration platform Albato (2026) demonstrates the effectiveness of a two-level architecture: the first level – trivial filtering of extreme values using hard thresholds; the second – LLM inference based on prompt engineering, where OpenAI ChatGPT and GigaChat models perform criterion-oriented analysis of extended responses. This approach minimises false positives and ensures contextual validity (Cohen’s kappa coefficient of agreement with expert assessment reaches 0.88) [4].

A study conducted by K. D. Muntinov [5] compared three generative models (ChatGPT-4, DeepSeek-R1, Grok-2) in assessing student essays in the humanities. It was found that for structured arguments, all models show high intraclass correlation ($ICC > 0.85$), but for creativity and novelty of ideas, systematic under-scoring is observed (especially for DeepSeek-R1), which is explained by the conservativeness of the training datasets. The conclusion is that LLMs are applicable for routine checking, but with mandatory calibration on original student texts [5]. It should be noted that K. D. Muntinov [5] analyses data from a Kazakhstani university; nevertheless, the findings on LLM behaviour are generalisable and relevant to the Russian context, since the models and the methodology of their application are comparable in both settings.

A prototype developed by master’s students at the AI Talent Hub (ITMO University) for Yandex Textbook implements an interactive Socratic dialogue mode: the AI asks clarifying questions, revealing the zone of proximal development (after L. S. Vygotsky) and diagnosing the level of understanding not by the final answer but by the reasoning trajectory. This signifies a transition from measurement-oriented to developmental assessment, where AI acts as a mediator of educational interaction.

Proctoring 2.0: the human-supported AI hybrid model

According to the State of Online Proctoring Report 2025 [6], the global online proctoring market reached USD 945 million in 2024, with projected growth to USD 2.2 billion by 2030. Meanwhile, the dominance of the university segment (53%) is gradually declining in favour of the corporate and government sectors, which are experiencing a compound annual growth rate (CAGR) of 18–22%. The key driver is not so much combating academic fraud as ensuring trust in certificates in a remote format.

Based on an analysis of industry sources, the following trends for 2025–2026 were identified:

- *Privacy-by-design*: students demand transparency in biometric data collection; institutions are moving from opt-out to opt-in models with explicit informed consent;
- *Hybrid control*: AI performs primary anomaly filtering, while a trained human specialist interprets the context, reducing false accusations of cheating to <2%;

- *LMS-first integration*: embedding proctoring into Moodle, Canvas, or Blackboard becomes a decisive factor in vendor choice;
- *Increased attention to user experience* (no plugin installation, easy verification, accessibility for persons with disabilities);
- *Asynchronous proctoring*: session recording with subsequent AI analysis is replacing synchronous live monitoring;
- *Decentralised verification*: use of blockchain for immutable logging [7].

A practical case of Rostelecom's solution for Sechenov University includes automatic screen tracking, facial recognition, and audio analysis with configurable scenarios – from individual control to mass examinations with 500+ participants. A key innovation is proactive notification of the student when suspicious behaviour is detected, rather than automatic test termination.

Learning analytics as a data-driven pedagogy paradigm

Learning analytics is defined as the measurement, collection, analysis, and reporting of data about learners and their contexts for the purpose of understanding and optimising learning and the environments in which it occurs [8]. Unlike business analytics in education, it is oriented towards formative feedback rather than mere reporting. The EDUCAUSE Horizon Report (2024) notes that analysis of the digital footprint (time on task, number of attempts, course navigation) allows the identification of “bottlenecks” in instructional design: if 70% of students view a particular lecture fragment three times and make errors in the same type of task, this correlates with unclear explanation rather than lack of ability. Implementation of recommender analytics reduced academic failure by 15–25% [9].

Logistic regression and random forest models are used to construct dropout risk models with predictors: frequency of LMS logins, timeliness of assignment submission, number of forum posts, and results of progressive tests. Prediction accuracy (AUCROC) reaches 0.82–0.89, enabling tutors to intervene 3–4 weeks before the final assessment [10]. In the research conducted by Zykova T.V., Vainshtein Yu.V., and Noskov M.V. [11], a competency graph analysis technology is proposed, whereby digital traces in Moodle are mapped to Bloom's taxonomy levels (knowledge, comprehension, application, analysis, synthesis, evaluation). Using machine learning methods, multidimensional visualisations are created in BI systems (Power BI, Tableau), providing an automated decision-support system for academic administrators.

Formative assessment and gamification: tools and limitations

Formative assessment is defined as the process of seeking and interpreting evidence used by teachers and students to determine the current level of achievement and to adjust learning activities [12]. Digital tools include micro-tests in Google Forms or LMS with automatic feedback, the “one-minute paper” (students record the main concept and an unclear question), and the “exit ticket” (answer to one key question before the end of the session). The results of a meta-synthesis covering 41 empirical studies (2012–2023) [13] show that the most frequently used e-assessment tools are electronic portfolios (42% of works), LMS-embedded tests (38%), and

web-based systems (20%). Digital tools increase student autonomy (Cohen's $d = 0.67$), but have limitations: poor suitability for assessing higher-order skills (critical thinking, creativity) and technical failures (noted in 23% of cases).

Gamification elements (badges, points, leaderboards) enhance engagement through dopaminergic reinforcement; however, M. D. Hanus and J. Fox [14] warn of the risk of extrinsic motivation – where internal interest is replaced by a chase for points. The optimal approach is to use gamification for routine tasks (terminology, algorithms) while retaining authentic assessment for complex cognitive tasks.

Assessment of digital competencies: standardisation and independent certification

The conceptual evolution of digital competencies has progressed from computer literacy (1980s–1990s) through ICT competence (2000–2015) to the current paradigm of digital competencies for life and professional activity, as captured in the DigComp 2.2 (2022) revision [15]. Key international standards include: DigComp (European Union), structured across five domains (information literacy, communication, content creation, safety, problem solving); ESCO (European Skills, Competences, Qualifications and Occupations), aimed at aligning educational outcomes with labour market demands; and SFIA (Skills Framework for the Information Age), organised into seven levels of responsibility. V. A. Sukhomlin and A. V. Yakushin [16] propose a model for designing flexible educational trajectories based on individual students' digital competence profiles.

A typical Russian example is the practice of the National Research University Higher School of Economics, where all first-year students take an independent digital literacy examination (60 minutes with proctoring). This test, developed on the basis of professional standards, covers humanities subjects that require proficiency in big data tools and AI technologies. Successful completion results in a certificate recognised by employers.

The unified portal I-EXAM.RU, administered by the Research Institute for Monitoring the Quality of Education, provides a cloud-based solution for large-scale testing, including AI proctoring and automatic generation of tasks with adaptive difficulty levels based on Item Response Theory (IRT). This system is used for both internal and external customised independent assessment in more than two hundred Russian universities. It should be clarified that in Russian regulatory practice there are no state platforms for testing digital competencies in the sense understood in countries with centralised certification systems. The I-EXAM.RU platform and similar solutions are organisations performing independent assessment functions, and their activities are not directly normatively anchored in FSES, which describe educational outcomes at the level of general competencies without specifying the instrumentation for their measurement.

Transformation of the teacher's role and the design of AI assistants

Changes in teacher professional competencies

The task of creating flexible intelligent learning systems has gained particular urgency with the advent of generative neural network models, which not only simplify the development of educational content but also substantially transform

established approaches to organising students' independent work. Researchers agree that the integration of AI into the educational process must be carried out judiciously and thoughtfully, without substituting concrete pedagogical functions [17–19]. Among the technological competencies required of the modern educator, both the Russian scholar P. V. Sysoev [20] and the international scholars S. Lee and K. Song [21] place particular emphasis on the ability to construct effective prompts when working with generative models. This positions the teacher as a technological moderator who helps students formulate queries – a function inextricably linked to the capacity to critically evaluate the outputs produced by generative systems [22]. Educators possessing such competencies are naturally able to develop students' critical thinking – a fundamental quality in an environment saturated with AI-generated texts, images, and videos [23–25].

Generation of didactic materials and quality assessment

It is worth noting that generative models are actively used by university teachers to create practically the full spectrum of didactic materials, including course syllabi, lecture and seminar plans, written texts, presentations, and learning tasks [26, 27]. At the same time, a current problem is the assessment of the quality of AI-generated content, especially in mathematical and computational disciplines. Research shows that the quality of such content can vary considerably, remaining acceptable not only for brief explanations or test items but even for describing approaches to complex problems; however, achieving reliable results requires the use of detailed prompts that take into account the specific characteristics of the generative model in use [28–31]. The generative mechanism itself requires mandatory expert evaluation of the obtained results [32]; to this end, a hierarchical system of twenty weighted indicators has been proposed, reflecting content relevance to the original prompt, stylistic quality, and user and technical characteristics [33].

AI assistants as tools for personalised support

The concept of platforms that use AI to support students' learning activities and free up teachers' time for genuinely pedagogical tasks underpins the design of AI assistants, understood as adaptive automated learning systems with feedback capabilities implemented via AI technologies [34–38]. A prototype of such an assistant, developed at the School of Computer Science of Tyumen State University [38], includes variable didactic materials, self-study scenarios, interaction algorithms for both students and teachers, and a digital footprint analysis subsystem. Its development confirmed the necessity of comprehensive pedagogical modelling and the critical importance of involving teachers as lead experts in the design and testing phases.

Challenges and ethical regulations

E-assessment tools are poorly suited to diagnosing higher-order skills such as synthesis, evaluation, and creativity, as these require semantic understanding and contextual sensitivity that current algorithms cannot provide [13]. A mini-review conducted by Z. Zulpykhar, M. Rakhmetov, B. Jugembayeva et al. [39], focusing on Ibero-America and Kazakhstan, highlights the following ethical issues: algorithmic

bias (models trained on data from privileged institutions systematically lower scores for students from rural schools); the “black box” problem (lack of explainable AI – XAI – generating distrust and appeals); data leaks (biometric proctoring records are classified as sensitive personal data); and the digital divide, which places students without reliable internet access or a quiet study space at a structural disadvantage. Recommendations include the adoption of ethical codes for AI use in education, mandatory model auditing for bias, and retention of students’ right to appeal with human involvement. Many technological challenges in this area remain unresolved due to the continuous development of generative models and the methods of working with them.

Discussion

The systematic review of assessment technologies in higher online education allowed not only the cataloguing of existing practices – including assessment using large language models and AI, proctoring, learning analytics, formative assessment, gamification, independent certification of digital competencies, and AI assistants – but also the identification of their internal evolution logic, driven by a paradigmatic shift in pedagogical measurement: from discrete knowledge recording to context-dependent analysis of learning activity.

The analysis shows that Russian universities and EdTech platforms [4] are actively adapting global approaches to adaptive testing (IRT), assessment of extended responses using large language models, and data analytics. However, unlike the USA and EU member states, where formative assessment with peer evaluation elements predominates [12, 13], Russia still favours summative assessment and centralised examinations with strict proctoring requirements. This is reflected in the widespread adoption of systems such as I-EXAM.RU and mass proctoring solutions from Rostelecom, which aligns with state policy to ensure academic integrity in distance learning formats.

Direct copying of foreign models, for example Western formative assessment systems applied without considering Russian examination culture, has proved largely ineffective. In contrast, successful cases – including hybrid AI-assisted human-supported proctoring, interactive Socratic dialogue implemented in Yandex Textbook, and the two-level LLM verification system in Albato [4] – illustrate the emergence of genuinely hybrid systems. *Hybridity* in this context is understood as a combination of automated testing (including LLM assessment) with elements of peer assessment and electronic portfolios, as well as the integration of machine analysis and human interpretation in proctoring and feedback procedures. Such hybridity is not a temporary compromise but a sustainable adaptation to the demands of the modern educational environment.

The thesis on ethical risks – encompassing algorithmic bias, the black-box problem, and the digital divide – is fully supported by both international meta-analyses [13, 39] and the findings of this review. In the Russian context, the digital di-

vide, manifested in unequal internet speeds and lack of suitable study conditions, is aggravated by regional disparities, requiring additional compensatory measures.

At the micro-level, comparing individual technologies revealed the following patterns. In LLM-based assessment, both Russian and international practice reflect a transition from discrete verification to semantic analysis. However, while international studies (e.g. on GPT-4 models) more often focus on formative feedback, Russian research emphasises summative assessment outcomes and minimisation of false positives [4]. The hybrid “AI plus human” model and the shift towards asynchronous monitoring are global trends [6]. Learning analytics is used in both Western and Russian contexts [8, 9, 11] for dropout prediction and pedagogical design optimisation, though Russian approaches [11] pay noticeably more attention to competency graph analysis and alignment with Bloom’s taxonomy, which may reflect traditions of fundamental pedagogical modelling.

A key difference between Russian and Western practices in applying assessment technologies lies in the degree of centralisation. In Russia, independent certification of digital competencies is typically implemented through organisations performing independent assessment functions (e.g. I-EXAM.RU, HSE University) and is methodologically tied to federal state educational standards. However, as noted above, FSES do not contain detailed requirements for the instrumentation of digital competency assessment, so the connection between platforms and standards is methodological rather than normative. In the USA and the EU, decentralised models dominate, including micro-certificates from Coursera and edX, while DigComp serves as a recommended framework rather than a mandatory standard.

The review also demonstrates that academic integrity in an online environment can be ensured not only through punitive measures such as proctoring but also through the very design of assessment instruments, including unique task formulations, open-ended questions, and time constraints. Hybrid proctoring, combining AI-based filtering with human interpretation, reduces false accusations to less than 2% [6] and currently represents an optimal balance between rigour and fairness. Personalised feedback is now achievable through learning analytics and AI assistants [38], which analyse digital footprints and generate recommendations. Effective practice [12] suggests that AI-generated recommendations should be interpretable under the XAI principle and accompanied by the possibility of appeal to the instructor. Data protection requires the implementation of privacy-by-design principles, entailing the collection of only necessary biometric data, encryption, and limited retention periods.

Recommendations include the adoption of ethical codes for AI use in education, mandatory auditing of models for bias and the student’s right to human appeal. Some issues related to ethical compliance, legal regulation, and information security are addressed at the institutional level; however, many technological problems remain open due to the continuous evolution of both generative models and the methods for working with them.

Conclusion

The review enables the identification of the main directions of evolution in assessment technologies for higher online education. There is a movement *from verification to understanding*, as LLMs and conversational AI shift the focus of assessment from answer checking to diagnosing cognitive processes. There is a movement *from surveillance to support*, as proctoring evolves from panoptic control (after M. Foucault) to a hybrid model prioritising privacy. There is a movement *from outcome to process*, as learning analytics makes assessment continuous, predictive, and proactive. Finally, there is a movement *from universality to personalisation*, as adaptive testing tailors itself to individual learning trajectories.

In accordance with the research questions posed at the outset, the following concise answers can be formulated based on the analysis:

Question 1. Which assessment technologies are used in Russia and abroad?

Both systems employ: automated testing (including LLM-based), proctoring (hybrid and asynchronous), learning analytics, formative assessment with gamification elements, independent certification of digital competencies, and AI assistants. Russia is dominated by centralised examinations with strict proctoring (I-EXAM. RU, Rostelecom solutions), while Western countries more often use decentralised formative approaches (portfolios, peer assessment, micro-credentials).

Question 2. What specific implementation features are determined by cultural, pedagogical, and institutional factors?

Russian practice is characterised by: (a) a focus on summative assessment and a state examination culture; (b) a methodological linkage to FSES (without strict normative regulation of assessment instruments); (c) a high degree of centralisation of certification and control; (d) pronounced regional disparities in infrastructure access. Western models are more decentralised, oriented towards formative feedback and individual trajectories, but also face algorithmic bias and digital divide issues.

Question 3. Which methods are most effective for different competency types?

Automated tests and LLMs perform well for subject knowledge and structured arguments ($ICC > 0.85$ for routine tasks), but are poorly suited for metacognitive skills – creativity, critical thinking, synthesis (systematic under-scoring is observed). For higher-order skills, authentic tasks (projects, essays, portfolios) with mandatory human involvement in assessment are required.

Question 4. How can academic integrity and personalised feedback be ensured?

Academic integrity is ensured through: hybrid proctoring (false accusations <2%), task design (unique formulations, time limits), and digital footprint analytics (risk prediction, early intervention). Personalised feedback is realised via AI assistants and learning analytics, generating interpretable recommendations with the

possibility of appeal to the instructor. Data protection builds on privacy-by-design principles (data minimisation, encryption, limited retention).

References

1. Zawacki-Richter O., Marín V.I., Bond M., Gouverneur F. Systematic review of research on artificial intelligence applications in higher education: where are the educators? *International Journal of Educational Technology in Higher Education*. 2019;16(1):1–27. doi:10.1186/s41239-019-0171-0
2. Crompton H., Burke D. Artificial intelligence in higher education: the state of the field. *International Journal of Educational Technology in Higher Education*. 2023;20(1):22. doi:10.1186/s41239-023-00392-8
3. Bearman M., Ryan J., Ajjawi R. Discourses of artificial intelligence in higher education: a critical literature review. *Higher Education*. 2023;86(3):567–585. doi:10.1007/s10734-022-00937-2
4. Vlasov D.V. Automation of student testing using generative artificial intelligence and modern integration platforms. *Elektronnyy nauchno-metodicheskiy zhurnal "Pedagogika informatiki" = Electronic Scientific and Methodological Journal "Pedagogy of Informatics"*. 2025;1–2. (In Russ.) Accessed April 28, 2026. http://pcs.bsu.by/2025_1-2/3ru.pdf
5. Muntinov K.D. Applying LLMs like ChatGPT, Deepseek, Grok for student work evaluation. *Vestnik Severo-Kazakhstanskogo universiteta imeni Manasha Kozybaeva = Bulletin of Manash Kozybayev North Kazakhstan University*. 2025;2(66):220–230. (In Russ.) doi:10.54596/10.54596/2958-0048-2025-2-220-230
6. Integrity Advocate. *State of Online Proctoring Report 2025*. 2025. Accessed April 28, 2026. <https://integrityadvocate.com/report2025>
7. Isaeva E.S. Modern LMS platforms for distance education: analysis and comparison. *Pedagogika. Voprosy teorii i praktiki = Pedagogy. Theory and Practice*. 2021;6(6):1045–1050. (In Russ.)
8. Mironova Yu.N. Using remote technologies during classes: LMS MOODLE, GOOGLE CLASSROOM, MICROSOFT TEAMS. *Azimat nauchnykh issledovaniy: pedagogika i psikhologiya = Azimuth of Scientific Research: Pedagogy and Psychology*. 2020;9(4):182–185. (In Russ.) doi:10.26140/anip-2020-0904-0037
9. Pelletier K., McCormack M., Muscanell N., Reeves J., Robert J., Arbino N. *2024 EDUCAUSE Horizon Report: Teaching and Learning Edition*. Boulder (CO): EDUCAUSE; 2024. 46 p. Accessed April 28, 2026. <https://library.educause.edu/resources/2024/5/2024-educause-horizon-report-teaching-and-learning-edition>
10. Fahd K., Venkatraman S., Miah Sh.J., Ahmed Kh. Application of machine learning in higher education to assess student academic performance, at-risk and attrition: a meta-analysis of literature. *Education and Information Technologies*. 2022;27:3743–3775. doi:10.1007/s10639-021-10741-7
11. Zykova T.V., Vainshtein Yu.V., Noskov M.V. Assessment of educational results in the e-learning system based on Bloom's taxonomy. In: *Novye obrazovatel'nye strategii v otkrytom tsifrovom prostranstve. Sbornik nauchnykh statey po materialam mezhdunarodnoy nauchno-prakticheskoy konferentsii = New Educational Strategies in the Open Digital Space. Collection of Scientific Papers Based on the Materials of the International Scientific and Practical Conference*. St Petersburg: Asterion Scientific and Information Technology Centre; 2025:51–56. (In Russ.) Accessed April 28, 2026. <https://elibrary.ru/item.asp?id=82273842&pf=1>
12. Black P., Wiliam D. Assessment and classroom learning. *Assessment in Education: Principles, Policy & Practice*. 1998;5(1):7–74. doi:10.1080/0969595980050102
13. Pusa E.T., Dinçer S. A meta-synthesis study on the use of e-assessment tools in education. *SAGE Open*. 2025;15(1):1–18. doi:10.1177/21582440251318459
14. Hanus M.D., Fox J. Assessing the effects of gamification in the classroom. *Computers & Education*. 2015;80:152–161. doi:10.1016/j.compedu.2014.08.019

15. Vuorikari R., Kluzer S., Punie Y. *DigComp 2.2: The Digital Competence Framework for Citizens (EUR 31006 EN)*. Publications Office of the European Union; 2022. doi:10.2760/115376
16. Sukhomlin V.A., Yakushin A.V. Concept and standards of digital skills and their application for developing educational trajectories. *Sovremennye informatsionnye tekhnologii i IT-obrazovanie = Modern Information Technologies and IT-Education*. 2025;21(3):201–215. (In Russ.) doi:10.25559/SITI-TO.021.202503.658-667
17. Schmidt D.A., Alboloushi B., Thomas A., Magalhaes R. Integrating artificial intelligence in higher education: perceptions, challenges, and strategies for academic innovation. *Computers and Education Open*. 2025;9:100274. doi:10.1016/j.caeo.2025.100274
18. Verboom A.D.P.R., Pais L., Zijlstra F.R., Oswald F.L., Santos N.R.D. Perceptions of artificial intelligence in academic teaching and research: a qualitative study from AI experts and professors' perspectives. *International Journal of Educational Technology in Higher Education*. 2025;22(1):46. doi:10.1186/s41239-025-00498-1
19. Zhang X., Liu H. Reflections on enhancing higher education classroom effectiveness through the introduction of large language models. *Journal of Modern Educational Research*. 2024;3:19. doi:10.53964/jmer.2024019
20. Sysoev P.V. A modern teacher's competence in the field of artificial intelligence: structure and content. *Vyshee obrazovanie v Rossii = Higher Education in Russia*. 2025;34(6):58–79. (In Russ.) doi:10.31992/0869-3617-2025-34-6-58-79
21. Lee S., Song K. Teachers' and students' perceptions of AI-generated concept explanations: implications for integrating generative AI in computer science education. *Computers and Education: Artificial Intelligence*. 2024;7:100283. doi:10.1016/j.caeai.2024.100283
22. Qian Y. Prompt engineering in education: a systematic review of approaches and educational applications. *Journal of Educational Computing Research*. 2025;63(7–8):1782–1818. doi:10.1177/07356331251322471
23. Melisa R., Ashadi A., Triastuti A., Hidayati S., Salido A., Ero P.E.L., et al. Critical thinking in the age of AI: a systematic review of AI's effects on higher education. *Educational Process: International Journal*. 2025;14:e2025031. doi:10.22521/edupij.2025.14.31
24. Hikmawati A., Mohammad N.K. Enhancing critical thinking with Gen AI: a literature review. *Buletin Edukasi Indonesia*. 2025;4(1):40–46. doi:10.56741/bei.v4i01.567
25. Salido A., Syarif I., Sitepu M.S., Suparjan, Wana P.R., Taufika R., et al. Integrating critical thinking and artificial intelligence in higher education: a bibliometric and systematic review of skills and strategies. *Social Sciences & Humanities Open*. 2025;12:101924. doi:10.1016/j.ssaho.2025.101924
26. Morales-Chan M., Amado-Salvaterra H.R., Hernandez-Rizzardini R. AI-driven content creation: revolutionizing educational materials. In: *Proceedings of the Eleventh ACM Conference on Learning @ Scale*. New York, NY: ACM; 2024:556–558. doi:10.1145/3657604.3664701
27. Khalil M., Liu Q., Jovanovic J. AI for data generation in education: towards learning and teaching support at scale. *British Journal of Educational Technology*. 2025;56(3):993–998. doi:10.1111/bjet.13500
28. Danilov A.V., Zaripova R.R., Lukoyanova M.A., Batrova N.I., Salekhova L.L. Effectiveness of prompt engineering strategies in generating mathematics educational content: an experimental study. *Science for Education Today*. 2025;4:113–135. (In Russ.) doi:10.15293/26586762.2504.05
29. Song T., Zhang H., Xiao Y. A high-quality generation approach for educational programming projects using LLM. *IEEE Transactions on Learning Technologies*. 2024;17:2296–2309. doi:10.1109/TLT.2024.3428956
30. Schorcht S., Buchholtz N., Baumanns L. Prompt the problem: investigating the mathematics educational quality of AI-supported problem solving by comparing prompt techniques. *Frontiers in Education*. 2024;9:1386075. doi:10.3389/feduc.2024.1386075

31. Meissner R., Pögel A., Ihsberner K., Grützmüller M., Tornack S., Thor A., et al. LLM-generated competence-based e-assessment items for higher education mathematics: methodology and evaluation. *Frontiers in Education*. 2024;9:1427502. doi:10.3389/educ.2024.1427502
32. Huang Q., Lv C., Lu L., Tu S. Evaluating the quality of AI-generated digital educational resources for university teaching and learning. *Systems*. 2025;13(3):174. doi:10.3390/systems13030174
33. Dickey E., Bejarano A. GAIDE: a framework for using generative AI to assist in course content development. In: *Proceedings of the 2024 IEEE Frontiers in Education Conference (FIE)*. IEEE; 2024:10893132. doi:10.1109/FIE61694.2024.10893132
34. Sinha A., Goyal S., Sy Z., Kuperus R., Dickey E., Bejarano A. BoilerTAI: a platform for enhancing instruction using generative AI in educational forums. In: *Proceedings of the 2024 IEEE Frontiers in Education Conference (FIE)*. IEEE; 2024:10893137. doi:10.1109/FIE61694.2024.10893137
35. Aperstein Y., Cohen Y., Apartsin A. Generative AI-based platform for deliberate teaching practice: a review and a suggested framework. *Education Sciences*. 2025;15(4):405. doi:10.3390/educsci15040405
36. Wessel M., Adam M., Benlian A., Majchrzak A., Thies F. Generative AI and its transformative value for digital platforms. *Journal of Management Information Systems*. 2025;42(2):346–369. doi:10.1080/07421222.2025.2467892
37. Zakharov A.A., Zakharova I.G., Shabalin A.M., Khanbekov Sh.I., Dzhililzoda D.B. Intelligent voice assistant as an example of inclusive design methodology implementation. *Obrazovanie i nauka = The Education and Science Journal*. 2024;26(3):149–175. (In Russ.) doi:10.17853/1994-5639-2024-3-149-175
38. Zakharov A.A., Zakharova I.G., Shabalin A.M., Nguyen Q.H. Designing an AI assistant to support independent learning in first- and second-year students. *Obrazovanie i nauka = The Education and Science Journal*. 2026;28(6):163–200. (In Russ.) doi:10.17853/1994-5639-2026-6-163-200
39. Zulpykhar Z., Rakhmetov M., Jugembayeva B., Kapanova D., Zhilmagambetova R. Assessment using artificial intelligence in higher education: innovations and ethical challenges in the Ibero-American and Kazakh contexts. 2026;11:1798126. *Frontiers in Education*. doi:10.3389/educ.2026.1798126

Список использованных источников

1. Zawacki-Richter O., Marín V.I., Bond M., Gouverneur F. Systematic review of research on artificial intelligence applications in higher education: where are the educators? *International Journal of Educational Technology in Higher Education*. 2019;16(1):1–27. doi:10.1186/s41239-019-0171-0
2. Crompton H., Burke D. Artificial intelligence in higher education: the state of the field. *International Journal of Educational Technology in Higher Education*. 2023;20(1):22. doi:10.1186/s41239-023-00392-8
3. Bearman M., Ryan J., Ajajwi R. Discourses of artificial intelligence in higher education: a critical literature review. *Higher Education*. 2023;86(3):567–585. doi:10.1007/s10734-022-00937-2
4. Власов Д.В. Автоматизация тестирования обучающихся средствами генеративного искусственного интеллекта и современных интеграционных платформ. *Электронный научно-методический журнал «Педагогика информатики»*. 2025;1–2. Режим доступа: http://pcs.bsu.by/2025_1-2/3ru.pdf (дата обращения: 28.04.2026).
5. Мунтинов К.Д. Применение LLM на примере ChatGPT, DeepSeek, Grok для оценивания работ студентов. *Вестник Северо-Казахстанского университета имени Манаша Козыбаева*. 2025;2(66):220–230. doi:10.54596/2958-0048-2025-2-220-230
6. Integrity Advocate. *State of Online Proctoring Report 2025*. 2025. Accessed April 28, 2026. <https://integrityadvocate.com/report2025>

7. Исаева Е.С. Современные LMS платформы дистанционного обучения: анализ и сравнение. *Педагогика. Вопросы теории и практики*. 2021;6(6):1045–1050.
8. Миронова Ю.Н. Использование дистанционных технологий при проведении занятий: LMS MOODLE, GOOGLE KCLASS, MICROSOFT TEAMS. *Азимут научных исследований: педагогика и психология*. 2020;9(4):182–185. doi:10.26140/anip-2020-0904-0037
9. Pelletier K., McCormack M., Muscanell N., Reeves J., Robert J., Arbino N. 2024 *EDUCAUSE Horizon Report: Teaching and Learning Edition*. Boulder (CO): EDUCAUSE; 2024. 46 p. Accessed April 28, 2026. <https://library.educase.edu/resources/2024/5/2024-educause-horizon-report-teaching-and-learning-edition>
10. Fahd K., Venkatraman S., Miah Sh.J., Ahmed Kh. Application of machine learning in higher education to assess student academic performance, at-risk and attrition: a meta-analysis of literature. *Education and Information Technologies*. 2022;27:3743–3775. doi:10.1007/s10639-021-10741-7
11. Зыкова Т.В., Вайнштейн Ю.В., Носков М.В. Оценка образовательных результатов в системе электронного обучения на основе таксономии Блума. *Новые образовательные стратегии в открытом цифровом пространстве. Сборник научных статей по материалам международной научно-практической конференции*. Санкт-Петербург: ООО Центр научно-информационных технологий Астерион; 2025:51–56. Режим доступа: <https://elibrary.ru/item.asp?id=82273842&prff=1> (дата обращения: 28.04.2026).
12. Black P., Wiliam D. Assessment and classroom learning. *Assessment in Education: Principles, Policy & Practice*. 1998;5(1):7–74. doi:10.1080/0969595980050102
13. Pusa E.T., Dinçer S. A meta-synthesis study on the use of e-assessment tools in education. *SAGE Open*. 2025;15(1):1–18. doi:10.1177/21582440251318459
14. Hanus M.D., Fox J. Assessing the effects of gamification in the classroom. *Computers & Education*. 2015;80:152–161. doi:10.1016/j.compedu.2014.08.019
15. Vuorikari R., Kluzer S., Punie Y. *DigComp 2.2: The Digital Competence Framework for Citizens (EUR 31006 EN)*. Publications Office of the European Union; 2022. doi:10.2760/115376
16. Сухомлин В.А., Якушин А.В. Концепция и стандарты цифровых навыков и их применение для разработки образовательных траекторий. *Современные информационные технологии и ИТ-образование*. 2025;21(3):201–215. doi:10.25559/SITITO.021.202503.658-667
17. Schmidt D.A., Alboloushi B., Thomas A., Magalhaes R. Integrating artificial intelligence in higher education: perceptions, challenges, and strategies for academic innovation. *Computers and Education Open*. 2025;9:100274. doi:10.1016/j.caeo.2025.100274
18. Verboom A.D.P.R., Pais L., Zijlstra F.R., Oswald F.L., Santos N.R.D. Perceptions of artificial intelligence in academic teaching and research: a qualitative study from AI experts and professors' perspectives. *International Journal of Educational Technology in Higher Education*. 2025;22(1):46. doi:10.1186/s41239-025-00498-1
19. Zhang X., Liu H. Reflections on enhancing higher education classroom effectiveness through the introduction of large language models. *Journal of Modern Educational Research*. 2024;3:19. doi:10.53964/jmer.2024019
20. Сысоев П.В. Компетенция современного педагога в области искусственного интеллекта: структура и содержание. *Высшее образование в России*. 2025;34(6):58–79. doi:10.31992/0869-3617-2025-34-6-58-79
21. Lee S., Song K. Teachers' and students' perceptions of AI-generated concept explanations: implications for integrating generative AI in computer science education. *Computers and Education: Artificial Intelligence*. 2024;7:100283. doi:10.1016/j.caeai.2024.100283
22. Qian Y. Prompt engineering in education: a systematic review of approaches and educational applications. *Journal of Educational Computing Research*. 2025;63(7–8):1782–1818. doi:10.1177/07356331251322471

23. Melisa R., Ashadi A., Triastuti A., Hidayati S., Salido A., Ero P.E.L., et al. Critical thinking in the age of AI: a systematic review of AI's effects on higher education. *Educational Process: International Journal*. 2025;14:e2025031. doi:10.22521/edupij.2025.14.31
24. Hikmawati A., Mohammad N.K. Enhancing critical thinking with Gen AI: a literature review. *Buletin Edukasi Indonesia*. 2025;4(1):40–46. doi:10.56741/bei.v4i01.567
25. Salido A., Syarif I., Sitepu M.S., Suparjan, Wana P.R., Taufika R., et al. Integrating critical thinking and artificial intelligence in higher education: a bibliometric and systematic review of skills and strategies. *Social Sciences & Humanities Open*. 2025;12:101924. doi:10.1016/j.ssaho.2025.101924
26. Morales-Chan M., Amado-Salvatierra H.R., Hernandez-Rizzardini R. AI-driven content creation: revolutionizing educational materials. In: *Proceedings of the Eleventh ACM Conference on Learning @ Scale*. New York, NY: ACM; 2024:556–558. doi:10.1145/3657604.3664701
27. Khalil M., Liu Q., Jovanovic J. AI for data generation in education: towards learning and teaching support at scale. *British Journal of Educational Technology*. 2025;56(3):993–998. doi:10.1111/bjet.13500
28. Данилов А.В., Зарипова Р.Р., Лукоянова М.А., Батрова Н.И., Салехова Л.Л. Эффективность стратегий промпт-инжиниринга в генерации математического образовательного контента: экспериментальное исследование. *Science for Education Today*. 2025;4:113–135. doi:10.15293/26586762.2504.05
29. Song T., Zhang H., Xiao Y. A high-quality generation approach for educational programming projects using LLM. *IEEE Transactions on Learning Technologies*. 2024;17:2296–2309. doi:10.1109/TLT.2024.3428956
30. Schorcht S., Buchholtz N., Baumanns L. Prompt the problem: investigating the mathematics educational quality of AI-supported problem solving by comparing prompt techniques. *Frontiers in Education*. 2024;9:1386075. doi:10.3389/educ.2024.1386075
31. Meissner R., Pögel A., Ihsberner K., Grützmüller M., Tornack S., Thor A., et al. LLM-generated competence-based e-assessment items for higher education mathematics: methodology and evaluation. *Frontiers in Education*. 2024;9:1427502. doi:10.3389/educ.2024.1427502
32. Huang Q., Lv C., Lu L., Tu S. Evaluating the quality of AI-generated digital educational resources for university teaching and learning. *Systems*. 2025;13(3):174. doi:10.3390/systems13030174
33. Dickey E., Bejarano A. GAIDE: a framework for using generative AI to assist in course content development. In: *Proceedings of the 2024 IEEE Frontiers in Education Conference (FIE)*. IEEE; 2024:10893132. doi:10.1109/FIE61694.2024.10893132
34. Sinha A., Goyal S., Sy Z., Kuperus R., Dickey E., Bejarano A. BoilerTAI: a platform for enhancing instruction using generative AI in educational forums. In: *Proceedings of the 2024 IEEE Frontiers in Education Conference (FIE)*. IEEE; 2024:10893137. doi:10.1109/FIE61694.2024.10893137
35. Aperstein Y., Cohen Y., Apartsin A. Generative AI-based platform for deliberate teaching practice: a review and a suggested framework. *Education Sciences*. 2025;15(4):405. doi:10.3390/educsci15040405
36. Wessel M., Adam M., Benlian A., Majchrzak A., Thies F. Generative AI and its transformative value for digital platforms. *Journal of Management Information Systems*. 2025;42(2):346–369. doi:10.1080/07421222.2025.2467892
37. Захаров А.А., Захарова И.Г., Шабалин А.М., Ханбеков Ш.И., Джалилзода Д.Б. Интеллектуальный голосовой помощник как пример реализации методологии инклюзивного дизайна. *Образование и наука*. 2024;26(3):149–175. doi:10.17853/1994-5639-2024-3-149-175
38. Захаров А.А., Захарова И.Г., Шабалин А.М., Нгуен К.Х. Проектирование ИИ-ассистента для сопровождения самостоятельной работы студентов младших курсов. *Образование и наука*. 2026;28(6):163–200. doi:10.17853/1994-5639-2026-6-163-200

39. Zulpykhar Z., Rakhmetov M., Jugembayeva B., Kapanova D., Zhilmagambetova R. Assessment using artificial intelligence in higher education: innovations and ethical challenges in the Ibero-American and Kazakh contexts. 2026;11:1798126. *Frontiers in Education*. doi:10.3389/feduc.2026.1798126

Information about the authors:

Olesya Yu. Digtyar – Cand. Sci. (Education), Associate Professor, Department of English for Professional Communication, Financial University under the Government of the Russian Federation, Moscow, Russian Federation; ORCID 0000-0002-1263-6204, Scopus Author ID 57211486394, ResearcherID IVV-5431-2023, SPIN-code 4468-7222. E-mail: OYDigtyar@fa.ru

Natalia G. Kondrakhina – Cand. Sci. (Philology), Associate Professor, Department of English for Professional Communication, Financial University under the Government of the Russian Federation, Moscow, Russian Federation; ORCID 0000-0003-3299-2617, Scopus Author ID 57195769554, SPIN-code 4893-3451. E-mail: nkondrakhina@fa.ru

Tatyana A. Tantsura – Associate Professor, Department of English for Professional Communication, Financial University under the Government of the Russian Federation, Moscow, Russian Federation; ORCID 0000-0003-3734-5670, Scopus Author ID 57207794546, ResearcherID D-9953-2015. E-mail: ttancyra@yandex.ru

Ekaterina E. Kuvshinova – Cand. Sci. (History), Associate Professor, Department of English for Professional Communication, Financial University under the Government of the Russian Federation, Moscow, Russian Federation; ORCID 0000-0001-5974-2875, Scopus Author ID 57205238712, ResearcherID GWV-5937-2022. E-mail: EEKuvshinova@fa.ru

Conflict of interest statement. The authors declare that there is no conflict of interest.

Received 12.03.2026; revised 23.07.2026; accepted for publication 03.08.2026.

The authors have read and approved the final manuscript.

Информация об авторах:

Дигтяр Олеся Юрьевна – кандидат педагогических наук, доцент кафедры английского языка и профессиональной коммуникации Финансового университета при Правительстве Российской Федерации, Москва, Российская Федерация; ORCID 0000-0002-1263-6204, Scopus Author ID 57211486394, ResearcherID IVV-5431-2023, SPIN-код 4468-7222. E-mail: OYDigtyar@fa.ru

Кондрахина Наталья Геннадиевна – кандидат филологических наук, доцент кафедры английского языка и профессиональной коммуникации Финансового университета при Правительстве Российской Федерации, Москва, Российская Федерация; ORCID 0000-0003-3299-2617, Scopus Author ID 57195769554, SPIN-код 4893-3451. E-mail: nkondrakhina@fa.ru

Танцура Татьяна Анатольевна – доцент кафедры английского языка и профессиональной коммуникации Финансового университета при Правительстве Российской Федерации, Москва, Российская Федерация; ORCID 0000-0003-3734-5670, Scopus Author ID 57207794546, ResearcherID D-9953-2015. E-mail: ttancyra@yandex.ru

Кувшинова Екатерина Евгеньевна – кандидат исторических наук, доцент кафедры английского языка и профессиональной коммуникации Финансового университета при Правительстве Российской Федерации, Москва, Российская Федерация; ORCID 0000-0001-5974-2875, Scopus Author ID 57205238712, ResearcherID GWV-5937-2022. E-mail: EEKuvshinova@fa.ru

Информация о конфликте интересов. Авторы заявляют об отсутствии конфликта интересов.

Статья поступила в редакцию 12.03.2026; поступила после рецензирования 23.07.2026; принята в печать 03.08.2026.

Авторы прочитали и одобрили окончательный вариант рукописи.